

AUTOMATIC GAIT RECOGNITION FOR HUMAN ID AT A DISTANCE

Final Technical Report
by

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Summary:

Recognising people by their gait is a biometric of increasing interest. Now, analysis has progressed from evaluation by few techniques on small databases with encouraging results to large databases and still with encouraging results. The potential of gait as a biometric was encouraged by the considerable amount of evidence available, especially in biomechanics and literature.

This report describes research within the Human ID (HiD) at a Distance program sponsored by the Defense Advanced Projects Research Agency through the European Research Office of the U.S. Army at the University of Southampton from 2000-2004. The research program was essentially designed to explore the capability of basic of gait as a biometric and potential for translation from a laboratory to a real world scenario. By development of specialized databases, by development of new techniques and by evaluation of laboratory and real-world data we contend that these objectives have indeed been achieved. There is a considerable volume of subsidiary developments not just of new computer vision techniques but also of approaches for spatiotemporal image analysis, particularly targeted at the modeling and understanding of human movement through image sequences. The ongoing interest in gait in a biometric is in a large part the wider remit of the analysis of human motion by computer vision techniques and due to the capability of gait as a biometric, as demonstrated by the results achieved by the HiD program

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1 Introduction and Background

1.1 Gait as a Biometric

A unique advantage of gait as a biometric is that it offers potential for recognition at a distance or at low resolution, when other biometrics might not be perceivable[3]. Further, it is difficult to disguise gait without hampering progress, which is of particular interest in scene of crime analysis. Recognition can be based on the (static) human shape as well as on movement, suggesting a richer recognition cue. Further, gait can be used when other biometrics are obscured – criminal intent might motivate concealment of the face, but it is difficult to conceal and/or disguise motion as this generally impedes movement.

There is much evidence to support the notion of using gait to recognize people. Shakespeare made several references to the individuality of gait, e.g.:

“For that John Mortimer....in face, in gait in speech he doth resemble” (Henry IV/II)

Further, the biomechanics literature makes similar observations:

“A given person will perform his or her walking pattern in a fairly repeatable and characteristic way, sufficiently unique that it is possible to recognize a person at a distance by their gait” [4]

Similar observations can be found elsewhere, even in contemporary literature. Early medical studies [5] established many of the basic tenets of gait analysis. These studies again suggested that gait appeared unique to subjects. Studies in psychology have progressed from establishing how humans can recognize subjects’ motion [6], to recognizing friends. Early approaches used marker-based technology, but a later one used video imagery [7], also showing discrimination ability in poor illumination conditions. As such there is much support for the notion of gait as a biometric.

1.2 Recognising People by their Gait

Prior to the HiD program, the approaches to recognizing people by gait were largely limited to using more standard techniques processing silhouettes and evaluated on small databases (containing 10 subjects or less). These included analyzing subjects’ trajectories [8], Principal Components Analysis (PCA) [9], moments (of optical flow) [10] and a combination of PCA with Canonical Analysis (CA) [11]. At that stage, only one approach had used a model to analyze leg movement [12] as opposed to using human body shape and movement. This pattern is reflected in the current approaches which largely are due to research within the HiD program and all but one are based on analysis of silhouettes, including: the University of Maryland’s (UM’s) deployment of hidden Markov models [13] and eigenanalysis [14]; the National Institute for Standards in Technology / University of South Florida’s (NIST/USF’s) baseline approach matching silhouettes [15]; Georgia Institute of Technology’s (GaTech’s) data derivation of stride pattern [16]; Carnegie Mellon University’s (CMU’s) use of key frame analysis for sequence matching [17]; Massachusetts Institute of Technology’s (MIT’s) ellipsoidal fits [18]; Curtin’s use of Point Distribution Models [19] and the Chinese Academy of Science’s eigenspace transformation of an unwrapped human silhouette [20]. Only the

latter two Institutions were not involved in the HiD program. These have shown promise for approaches that impose low computational and storage cost, together with deployment and development of new computer vision techniques for sequence-based analysis. These same factors have also motivated our own new approaches that range from a baseline-type approach by measuring area [21], to extension of technique for object description including symmetry [22] and statistical moments [23]. These have all been evaluated on the data recorded within the Human ID program and the latter two were used within the Gait Challenge evaluations. Further, we have extended our model-based technique to include full limb movement [24] and show how a model-based approach can facilitate greater application capabilities and is as yet the only approach that can handle subjects who are walking or running.

1.3 Database Development

The use of relatively small databases by the early approaches was largely enforced by limited computational and storage requirements at that time. It has been very encouraging to note that similar levels of discrimination can be achieved on the much larger datasets now available. Naturally, the success and evolution of a new application relies largely on the dataset used for evaluation. Accordingly, it is encouraging to note the rich variety of data that has been developed, all with the HiD program. These approaches include: UM's surveillance data [13]; NIST/ USF's outdoor data, imaging subjects at a distance [25]; GaTech's data combines marker based motion analysis with video imagery [16]; CMU's multi-view indoor data [26]; and University of Southampton's data [27] which combines ground truth indoor data (processed by broadcast techniques) with video of the same subjects walking in an outdoor scenario (for computer vision analysis). As the HiD program commenced in 2000, this was contemporaneous with the advent of low cost Digital-Video (DV) technology and GaTech, MIT and Southampton chose to acquire imagery using new DV cameras.

The attention in the face recognition community has only recently progressed to factors which give intra-person variation such as age and expression. As gait is a behavioural biometric there is much potential for within-subject variation. This includes footwear, clothing and apparel. Application factors concern deployment via computer vision though none of the early databases allowed facility for such consideration, save for striped trousers in an early Southampton database (aiming to allow for assessment of validity of a model-based approach). Our new databases sought to include more subjects so as to allow for an estimate of inter-subject variation, together with a limited estimate of intra-subject variation thus allowing for better assessment of the potential for gait as a biometric which thus provided an assessment of the factors/ measurements which are most potent for recognizing a subject by the way he – or she – walks.

1.4 Progress and Achievements

1.4.1 Overall Progress

The main achievements of this research concern the evaluation of gait as a biometric and its ramifications. Much of the agenda for this research was specified with the Human ID at a Distance research programme for which there were meetings of the gait researcher team in the US approximately every four months, attended by Professor Nixon and Dr. Carter usually with Southampton's researchers in attendance. The first of these meetings specified the format for the gait data to be collected, later meetings concerned evaluation systems and the last meetings concerned evaluation results.

The evaluation of gait as a biometric initially concerned evaluation on our own and on other groups' data (for which our evaluations concerned the CMU and the Maryland data). The Southampton data required the construction of a gait laboratory, essentially a form of photographic studio for walking subjects. The gait laboratory essentially concerned a walking track and a treadmill which were viewed by a number of digital video camcorders. This required construction of specialised background and illumination arrangements. The volume of data required development of a GRID-enabled computing cluster initially of 12 machines. Two evaluations were specified within the Human ID gait program. The first was an analysis on a subset of the data collected across all groups; a later evaluation concerned the Gait Challenge which required development of software and technique to provide the fully automated analysis of data supplied by NIST. This data contained sequences of images of subjects walking around a defined outdoor track, in uncontrolled illumination. The extra volume of data required extension of the computing cluster to allow for timely analysis. The large volume of data required throughout the project mandated development of a 12 TB storage server and backup facilities; the need for efficacious data transfer mandated use of a dedicated FTP server.

The work was primarily achieved by research fellows: Dr. Michael Grant, Dr. Jamie Shutler, Mrs Layla Gordon, Dr. Richard French, Dr. Lee Middleton and Dr. Veres, who were employed by the program. The subsidiary research was achieved by research students who had other support for tuition fees and subsistence. Some temporary staff were employed to relieve mainstream researchers, particularly during data collection and preparation for analysis.

1.4.2 Major Contributions

The major contributions associated with Southampton's part of the Human ID at a Distance program are:

1. the establishment of the largest database of its kind of the evaluation of the potential of gait as a biometric both in terms of basic capability and in terms of capability for practical deployment by computer vision techniques [71, 72, 88, 91, 93, 112, 114, 115, 116, 117, 118, 119, 121, 122];

2. the establishment of a database with the largest number of covariate factors for gait which allows for estimation of intra-personal gait variation as well as for assessment of potency of gait measures for recognition purposes [71, 72, 88, 90, 116, 117, 118, 119, 121, 122];
3. the confirmation that gait has capability for biometric purposes not just in a laboratory environment, but also via deployment by using computer vision techniques, on the largest database currently available [43, 44, 45, 46, 47, 48, 49, 50, 52, 58, 62, 63, 64, 68, 73, 74, 75, 78, 80, 84, 85, 88, 89, 90, 91, 92, 93, 105, 107, 108, 109, 110, 111, 112, 114, 115, 116, 117, 118, 122, 125]; and
4. that recognizing people by gait concerns a combination of body shape and dynamics and the relative potency of these measures depends on the technique deployed [88, 90, 112, 114].

1.4.3 Technical Achievements

The technical achievements of Phase 1 of the proposed research [1] include:

- 1.1 Large, basic data set containing >100 subjects, covering the normal human population [55, 59, 60, 66, 71, 72, 114, 115, 116, 117, 118, 119, 121]
- 1.2 Small, in-depth data set of >10 individuals, extensively measured [71, 72, 88, 90, 116, 117, 118]
- 1.3 Results and scores from application of existing statistical and model based gait recognition strategies [43, 44, 45, 46, 47, 48, 49, 50, 52, 58, 62, 63, 64, 68, 73, 74, 78, 107, 108, 109, 111, 112, 114, 115, 116, 117, 118]
- 1.4 Reporting on analysis of the findings of 1.3, above, setting out the strengths and limitations of gait recognition in the context of the laboratory experiments described above [43, 44, 45, 46, 47, 48, 49, 50, 52, 58, 62, 63, 64, 68, 73, 74, 78, 107, 108, 109, 111, 112, 114, 115, 116, 117, 118]
- 1.5 Software developed for test purposes
- 1.6 Implementation of subject extraction [51, 67, 70, 84, 104, 113, 120]
- 1.7 Implementation of trajectory extraction/ correction [76, 78, 81, 106, 120]

Due to other requirements by the HiD program, we did not achieve

- 1.8 Evaluation of extraction, correction and other imaging modalities (thermal)

In Phase 2 of the program [2], we achieved:

- 2.1 Gait evaluation: evaluation of model-based and statistical analysis [75, 80, 84, 85, 88, 89, 90, 91, 92, 93, 105, 110, 111, 112, 122, 125]
- 2.2 Gait extraction and description: where the automated implementation was refined by enhancement to periodicity and tracking [85, 91, 105, 106, 110, 125]
- 2.3 3D Viewpoint Invariance: where we developed 3D appearance invariance and recognition unaffected by viewpoint. [54, 56, 121]

The latter of these topics is an ongoing research topic [121, 126]. Other achievements not specified in the original proposal, but specified later as part of the Human ID program include:

- 3.1 Analysis of other HiD data
- 3.2 Fully automated evaluation of NIST data [85, 92, 105, 110]
- 3.3 Provision to NIST of Southampton data in HBase format

1.4.4 Ancillary Contributions

Ancillary contributions include development and analysis of:

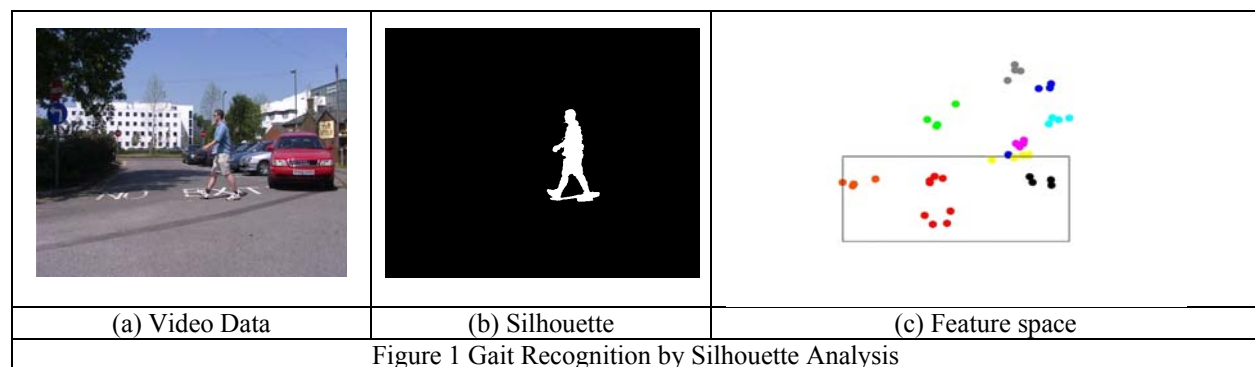
- a) the notion of temporal symmetry for recognition by gait [43, 47, 50, 63, 107, 116];
- b) temporal measures of area for recognition by gait [44, 46, 49, 73, 74, 108, 117];
- c) statistical moments for gait recognition [48, 114];
- d) model-based running and walking analysis for recognition [45, 52, 58, 62, 64, 68, 111, 115];
- e) a vision-based 3D gait analysis system [67, 113];
- f) a markerless gait analysis system [55, 59, 60, 66, 75, 80, 118];
- g) a new means for predicting inter-frame object movement and appearance [65, 69, 77, 79, 119];
- h) viewpoint invariant gait recognition [54, 56, 121];
- i) new approaches to background subtraction [83, 93, 122];
- j) new approaches to low-level feature extraction [82, 86, 87, 92, 124]; and
- k) a generalized approach to arbitrary articulated-object extraction in image sequences [78, 91, 125].

These contributions form the bulk of the research and have been published in conferences or in journals or as PhD theses and these are listed in Appendix 1, after the literature cited in this report, and contained in a separate Volume. Prizes associated with some of these publications are listed in Appendix 2.

2 Advances in Gait Description and Analysis

2.1 Holistic / Silhouette Approaches

Essentially, we seek to process video images, Fig. 1(a), to derive silhouettes of the moving subject, Fig. 1(b) from which we derive numbers that reflect the identity of the subject, Fig. 1(c). This then describes a subject, not just by shape but also by motion. As with the holistic approach developed prior to the HiD program [11], this is achieved [23] by reformulating a traditional description (by moments) to include motion (time) and applying it to a sequence of images. In Fig 1(c) there are 4 such sequences from each of 10 subjects in each cluster for three such measures. The clustering reflects that recognition by gait can indeed be achieved. Essentially, the measures derived by this way reflect that a subject can be recognized by their body shape and by the way they move. An important advantage of the newer approaches is that order is implicit in the image sequences: some holistic approaches prior to the HiD program would give the same result irrespective of the image order within the sequence.

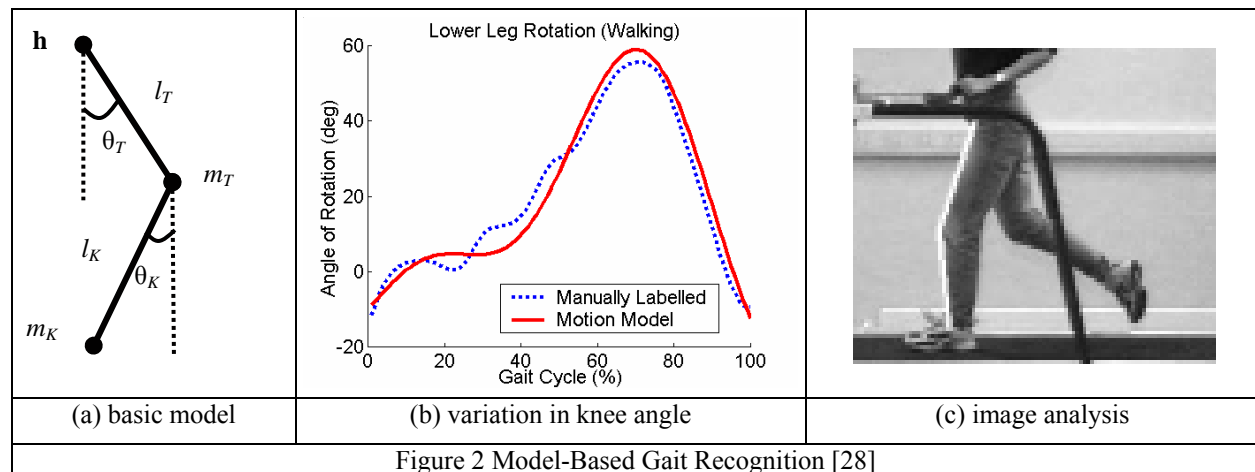


Similarly, inclusion of time within a symmetry calculation can include [22] contributions of spatial and temporal symmetry. This was achieved by refining a distance functional to include time as well as space whilst the other functionals (phase and intensity) remained unchanged. In application, the temporal symmetry is derived for a sequence of images first by edge detection. In common with other baseline approaches, we also sought to develop a fast technique with specificity to gait [21]. This is achieved by using masking functions that are convolved to give a time variant signal describing gait. As it is a measure of area, not only is it fast in implementation, but it also allows for specificity to gait by choice of the masks used.

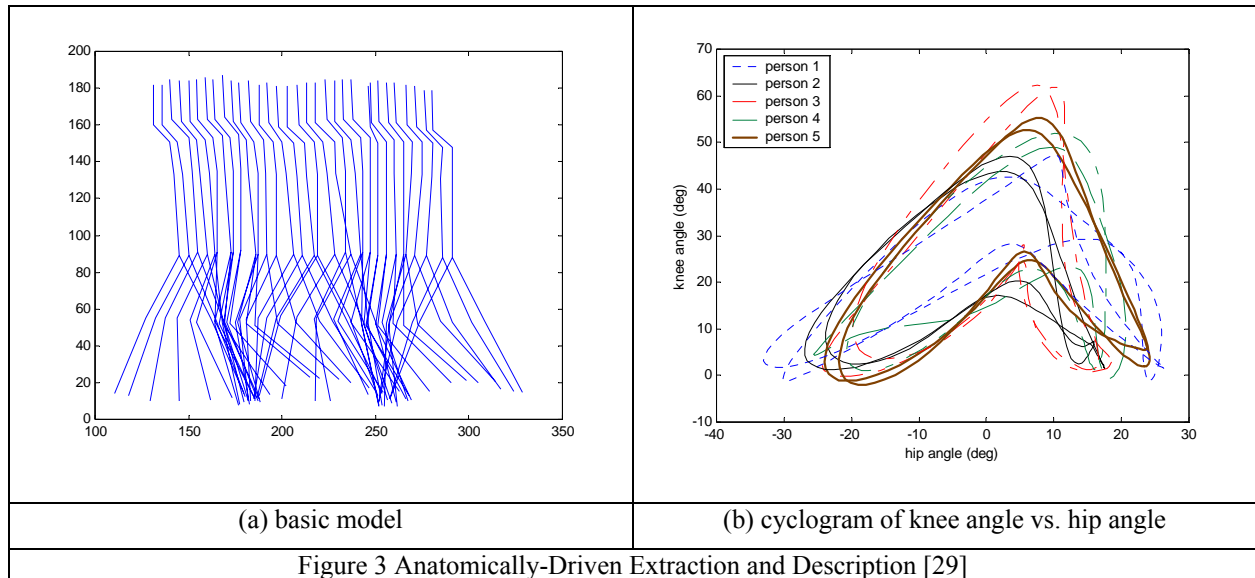
2.2 Model-Based Approaches

Prior to the Human ID program, the earliest model-based approach relied on the use of frequency components of a thigh's motion [12]. Naturally, this should also offer facility to model running as well as walking. Accordingly, in the HiD program, we extended the model to include both running and walking and to include the motion of the lower leg. This is unique in that models of the movement of the whole leg are used in a recognition approach and

since the approach can handle subjects who are walking or running. The approach uses the concept of bilateral symmetry of the motion of the two legs, and phase coupling between the constituent sections. The new model provides a unified model for walking and for running, without need for parameter selection [24]. The model is illustrated in Fig 2(a); the change in the knee angle θ_K with time is shown in Fig 2(b) superimposed on the analysis achieved by manual labelling. This can model successfully the motion of the thigh and the lower leg, for precise extraction of the thigh angle, and the lower leg angle, shown in Fig. 2(c). This was achieved by considering the thigh as a free pendulum, forcing the motion of the lower leg. This model has been shown to good effect on a separately developed database of subjects who were filmed walking and running. This showed greater variation in the styles of running, consistent with the forced motion within a running gait. Further, the transformation between walking and running was shown [28] to have better discriminatory capability than the individual measures, which appears to be since the transformation subsumes both running and walking.



In order to investigate the basic nature of gait, and the link between silhouette-based descriptions and the human skeleton, we have been developing an anatomically driven approach that employs new cyclic descriptions for recognition. This model has been demonstrated to good effect on small laboratory databases [29], its target application is our laboratory data to acquire better understanding of the nature, and description, of gait. The motion of the skeleton derived from a silhouette sequence is shown in Fig. 3(a) and the cyclogram derived from these new measures is shown in Fig. 3(b) which by its cyclical nature shows periodicity in the gait cycle and the difference between these cycles reflects the individuality associated with each person's (unique) gait.

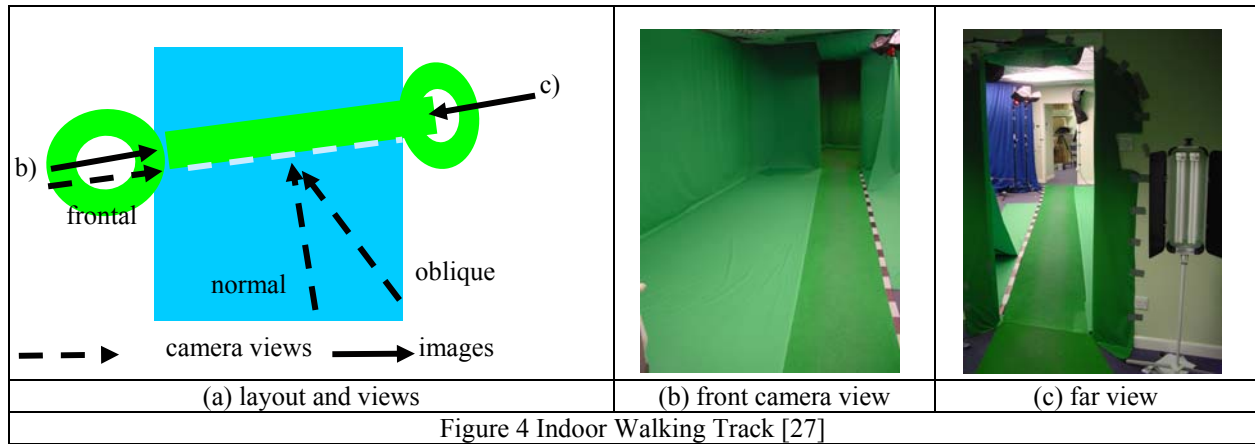


3 Analysing Recognition by Gait

3.1 The Southampton Database

3.1.1 Technological Considerations

Prior to the HiD program, databases had involved at most 10 subjects. One of the primary tasks in Southampton's part of the HiD program was to acquire a database of subjects, in number far exceeding that of the early approaches. We sought to acquire two main databases: one of over 100 subjects to examine inter-subject distance (the difference between individuals), the other is of 10 subjects and assesses intra-subject variance (the change within an individual subject). This allows us to investigate the fundamental paradigm of pattern recognition, namely the relationship between the within-class and the between-class distances for this governs how recognition capability can be achieved. Given that Digital Video (DV) is now an established technology at reasonable cost and since our evaluation of quality suggested that it could equal that of conventional video recording, and to reduce data volume, the members of HiD program chose to use DV [27]. We acquired images via the highest quality progressive scan and interlaced DV camcorders available at that time (late 2000). The database construction software was Python (and XML for labelling); recognition implementations use standard languages, primarily for reasons of speed.



Camera	Scan Type	View Angle	# subjects	Locality	Walk Surface
A	Progressive scan	Normal	116	Indoors	Track
D	Interlaced	Oblique	116	Indoors	Track
B	Progressive scan	Normal	116	Indoors	Treadmill
C	Interlaced	Oblique	116	Indoors	Treadmill
E	Progressive scan	Normal	116	Outdoors	Track
F	Interlaced	Oblique	116	Outdoors	Track

Table 1 Overview of Southampton's Large-Subject Gait Databases

Index	Scan Type	View Angle	Number of Subjects	Locality	Walk Surface
AS	Progressive Scan	Normal	12	Indoors	Track
BS	Interlaced	Oblique	12	Indoors	Track
GS	Progressive Scan	Inclined and Normal	12	Indoors	Track
HS	Progressive Scan	Frontal	12	Indoors	Track

Table 2 Overview of Southampton's Small-Subject Gait Databases

3.1.2 Database Design

The structure of the two main Southampton databases is given in Tables 1 and 2. The Large-Subject Databases allow for estimation of between-subject variation; the Small-Subject Databases allow for estimation of within-subject variation. A third database was constructed from between these two, by combining database A and database AS to provide a small number of subjects imaged at different times. The three main databases then expose variation between-classes; variation within classes; and variation due to time.

In order to provide an approximation to ground truth and to acquire imagery for application analysis, we chose to film subjects indoors and outdoors, respectively. Indoors, treadmills are most convenient for acquisition as long gait sequences can be acquired by their use though there is some debate as to how they can affect gait. Some studies hold that kinetics are affected rather than kinematics, but our experience with using untrained subjects and limitations on footwear and clothing motivated us to consider the track as the most suited for full analysis. The track was of the shape of a “dog’s bone”, shown in Fig. 4(a), so that subjects walked constantly and passed in front of the camera in both directions. The track was prepared with chromakey cloth (bright green, as this is an unusual clothes’ colour) and the background was illuminated by photoflood lamps, seen from either end in Figs. 4(b) and (c), viewed by cameras frontally, normally and at an oblique angle (an additional surveillance view is not shown). The arrangement enables chromakeyed subject separation from background, as in broadcast technology. On the treadmill, subjects were highlighted with diffused spotlights and the treadmill was set at constant speed and inclination, aimed to support a conventional walk pattern. Psychology suggested that all personnel should be outside the laboratory during recording, to avoid any embarrassment and any movement of the head during conversation. Further, a talk-only radio was used to ease familiarity with the laboratory. Placing a mirror in front of the treadmill aided balance and stopped the subject from looking at their feet and/or the treadmill control panel. Example images from the indoor data are shown in Fig. 5. A similar track layout was used outdoors, Fig. 1 (a), where the background contained a selection of objects such as foliage, pedestrian and vehicular traffic, buildings (also for calibration) as well as occlusion by bicycles, cars and other subjects.

The imagery for the large database was completed with a high resolution still image of each subject in frontal and profile views, allowing for comparison with face recognition and for good estimates of body shape and size. Further, ten subjects were filmed on the track wearing a variety of footwear and clothing, carrying a variety of objects and at different times, to allow for estimation of intra-subject variability. The initial track data was segmented into background and walking sequences and further labels were introduced for each heel strike and direction of walking. This information is associated with the data as XML; these labels include subject ingress, egress, direction of walk and heel-strikes, together with laboratory and camera set-up information recorded for each recording session. This allowed for basic analysis including manually imposed gait cycle labels. The treadmill and outside data was segmented into background and walk (including direction) data only.



The Southampton HiD database has now been used worldwide and a list of users registered so far for the database is included in Appendix 3.

3.2 Recognition by Gait

3.2.1 Overview

Our approaches process a sequence of images to provide a gait signature. Ideally, the sequence of images is taken from heel-strike to the next heel strike of the same foot. The holistic approaches require a silhouette to be derived, or optical flow (which describes motion), resulting in a set of connected points in each analysed image. These are then classified. Here we use the k -nearest neighbour approach to allow comparison with other approaches, whilst noting that more sophisticated classifiers can offer better performance, often in respect of generalization capability. The Euclidean distance metric is used to provide ranking lists describing the difference between signatures. Again, more sophisticated measures are available. In accordance with current practice - as used, defined and developed within the HiD programme - we used independent training, probe and gallery sets to develop sets of ranked lists and cumulative match scores.

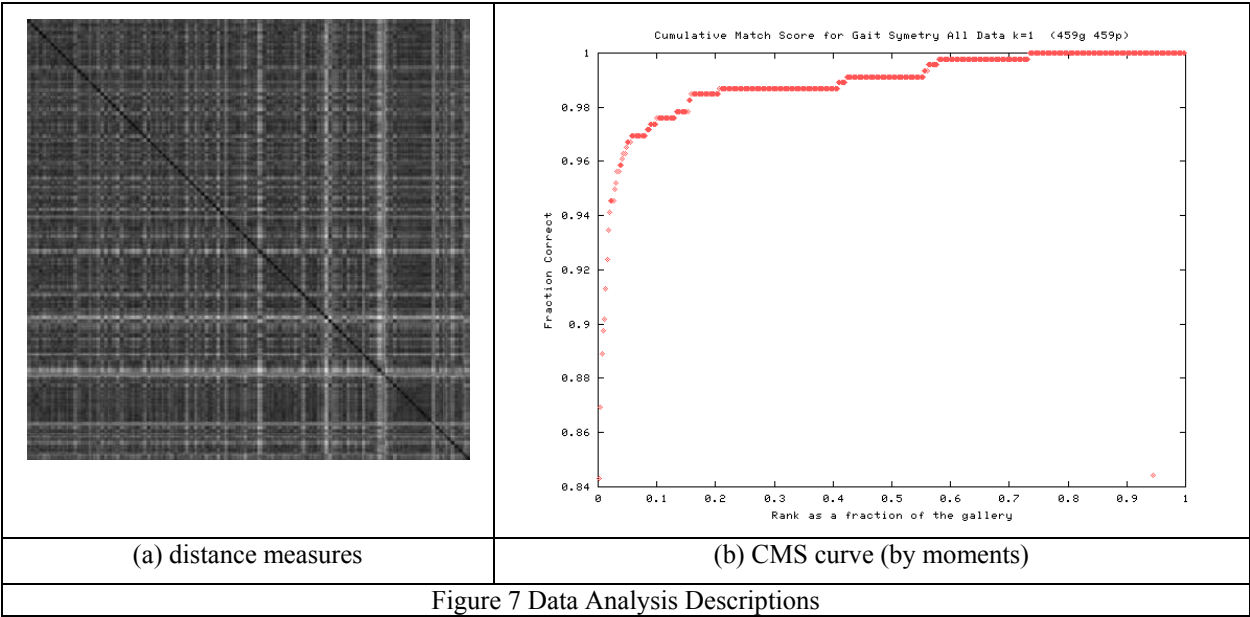
3.2.2 Analysis of Southampton Database – Recognition Capability

To date, different recognition approaches – all holistic - have been applied to our new data, all with encouraging results. These analysis of the database suggests that it has indeed met its design objectives. First, high gait recognition performances have been achieved on the largest yet number of subjects for gait, an overview of these results via analysis by symmetry can be seen in Fig. 6. Similar results were achieved not only by the new approaches developed within the HiD programme, but also by other approaches. The progression of these results reflects the gradual construction of the databases: the early versions of the database had a limited number of subjects and this was used in the early DARPA cross-evaluation. Later we developed the whole database, and it is this which finds world-wide use. It is of note that of the techniques developed at Southampton, symmetry has the most potent performance, moments have the greatest invariance properties whereas the area moments are formulated more for speed. These results show a recognition rate that is perhaps higher than originally anticipated. Other techniques equal this discriminatory capability [13, 15, 16, 30]. Further, results on outdoor data have been reported elsewhere [31] and we can now achieve similar results on laboratory and on outdoor data.

No. of Subjects	No. of Sequences	Classifier Result (%)	
		$k = 1$	$k = 3$
28	4 with 1 cycle	97	96
50	4 with 1 cycle	95	93
114	8 with 1 cycle	94	90

Figure 6 Progression of Recognition Results by Symmetry

An example distance analysis and cumulative match score (CMS) are shown in Figs. 7(a) and (b), respectively. The distance measures show that most subjects are clearly distinguished by their gait and most classes are highly disparate (black represents similarity and white is difference), but there is some potential for class confusion. Note that there is one band of gross dissimilarity: this concerns the analysis of childrens’ gait and even though this is known to be mature in medical terms, clearly was very different from adults’ gait. This is reflected by the CMS curve starting at over 80% but note that 98% correct of the probes are within nearly the first 10% of the gallery.



3.2.3 Human ID at a Distance: Gait Challenge

The DARPA gait program concentrated the efforts of a subsection of the Human ID program on gait recognition and in three main areas: new technique; new data; and evaluation, essentially taking gait from laboratory-based studies on small populations to large scale populations of real world data. This aimed specifically to test algorithms in a real scenario, on dta collected independently at NIST and distributed by DARPA. This data was single sequences of two views of a single subject walking round an elliptically shaped track. The data explored six covariate factors including different surfaces and different shoes. The video data was distributed as uncalibrated and without metadata (such as heel-stike labeling). The data is freely available for evaluation and it is very encouraging to see how research in gait has benefited from research in other biometrics: there is a range of scenarios, covariate and ground truth data already available. The challenge concerned analyzing this data so as to recognize people by the way they walked. An example frame from one sequence is shown in Fig. 8.



Figure 8: Example Frame from the Gait Challenge Data

Each of the gait teams in the Human ID at a Distance programme was tasked to analyze this data. The analysis was conducted by MIT, Maryland, Southampton, GaTech, CMU, and USF/ NIST. The Southampton group's approach was to develop a fully automated approach working from the raw video to generate recognition metrics. The stages in the Southampton approach were

- i) background extraction to separate moving features from the (largely) static background ;
- ii) to coalesce moving features via blob tracking and merging;
- iii) sequence identification to determine a single gait cycle;
- iv) two feature descriptions via symmetry detection and averaged silhouette analysis; and
- v) recognition via k -nearest neighbour analysis

An alternative approach, and one used by all other gait teams, was to use the supplied USF silhouettes and thereby omit stages i)-iii) and use only stages iv) and v). Recognition rates similar to those on other data have been reported, some of the example rates here are early [15, 33, 32, 36] with better results later. Some of the peak classification rates of the evaluations in the Human ID programme are given in Table 3.

	Viewpoint	Shoe
Maryland [36]	79	86
Carnegie Mellon [32]	98	90
MIT [34]	96	88
Southampton	93	88
USF [15]	87	76

Table 3: Example Gait Challenge Results

A more detailed analysis of the detailed results for the Southampton part of the gait challenge is shown in Table 2. The experiments refer to the different covariate factors: view concerns change in viewpoint, shoe concerns change in footwear, surface concerns the nature of the surface the subject walked on (either grass or concrete), time concerns imagery of the same subject gathered at a different time. By these results, recognition was best for change

in viewpoint and for which at best 75% correct recognition rate and 98% correct for the subject to be within the 5 closest matches. In fact, this is a pattern similar with the other approaches to the gait challenge analysis (except GaTech whose approach failed since the grass sometimes obscured the subjects' feet).

Exp.	Covariate	PI (%) (at rank)		PV (%) at PF = 1%			PV (%) at PF = 10%		
		1	5	UN	MAD	ZN	UN	MAD	ZN
A	View	75	98	65	60	52	88	98	95
B	Shoe	51	74	44	44	31	67	72	69
C	Shoe, View	46	78	32	27	19	65	70	65
D	Surface	19	57	5	14	11	44	51	48
E	Surface, Shoe	8	36	0	3	3	15	23	21
F	Surface, View	3	35	3	5	3	14	27	24
G	Surface, Shoe, View	10	46	7	12	7	32	39	39
H	Briefcase	30	67	9	25	17	44	58	55
I	Briefcase, Shoe	45	76	14	38	24	62	71	69
J	Briefcase, View	25	72	17	16	11	53	66	63
K	Time, Shoe, Clothes	3	20	0	3	3	10	20	17
L	Surface, Time, Shoe, Clothes	0	17	0	0	0	10	10	10

Table 4: Example Gait Challenge Results

The increase in recognition rate with the number of closest matches, the rank of the recognition process, is shown in Fig. 10 which reflects the analysis in Table 4, for the same covariates. It can be seen that most approaches can achieve 100% correct recognition, though on this analysis it did not appear possible to recognize the same subject appearing at different times. The Receiver Operator Characteristic confirms the potency of the gait measures on different viewpoints, and that the approach could not recognise correctly subjects appearing at different times. The overall conclusions were that the recognition performance was highly dependent on the quality of silhouettes used. As tasked to do, we did indeed provide a fully automated system and used this to recognise subjects by the way they walked and in outdoor data too [85, 92, 105, 110].

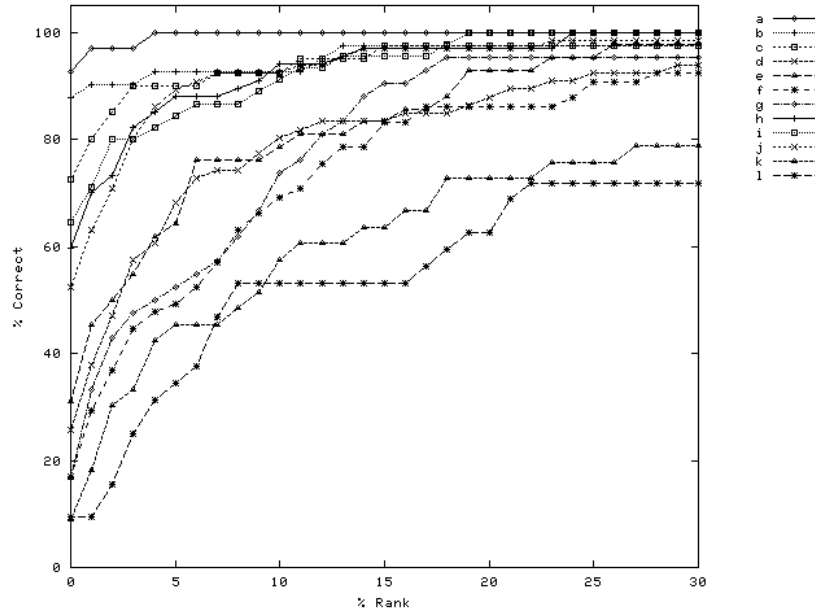


Figure 10: Cumulative Match Score: Gait Challenge

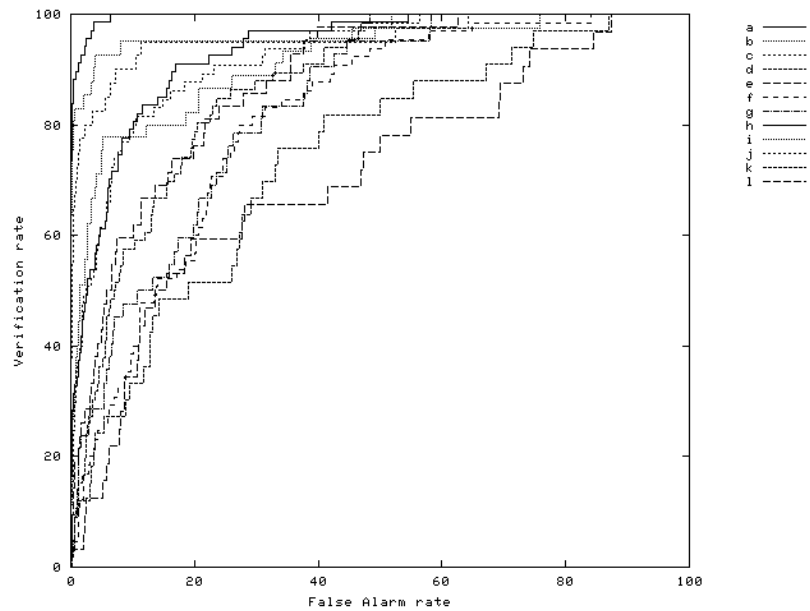


Figure 9: Receiver Operator Characteristic: Gait Challenge

3.2.4 Potency of Gait-Biometric Measurements

It is interesting that it is only recently face recognition has come to concentrate on feature potency. In this respect gait research has learned from face recognition since the databases were constructed with such an aim in mind. The

covariate database was recorded explicitly to explore variation in walking style. An alternative interpretation is that the database also allows for exploration of those factors which offer the most potent description of generalized walking. Accordingly the silhouettes for Southampton databases A, AS and a time version TS were analysed for potency[90].

Two of the simplest approaches were used to obtain a gait signature for a given sequence, aiming not to lose any information by the invariant properties say of symmetry or moments. First, a sum of all silhouettes in a full gait cycle was used to obtain an average appearance for each recorded sequence, which is simply the average of all the binary silhouettes which are centralized within each image. The alternative way used a differencing operation on adjacent silhouettes to obtain a basic estimate of motion.

First all three databases were analysed separately using ANOVA and PCA to find out which image information (features) is completely redundant, which features have a relatively high variation between the subjects, and how the original feature set could be reduced without a big reduction in the variance-explained and recognition rate. All three databases have redundant features and they are not necessarily all the same. This is important in application, since it suggests areas on which a camera or feature extraction approach might concentrate. However, to jointly compare databases A, AS and TS the datasets have to be reduced to the same number of features. Therefore, shared important features between three databases were determined and how the reduction to these features in three databases affect recognition rate was investigated. The recognition rate was calculated using Euclidean distance and the nearest neighbour rule. A more sophisticated classifier was not used since the important factor was only the relative reduction/increase in recognition rate at this stage. It is worth noticing that to be able to display all results in an easily understandable way, the initial feature sets were extracted from 64×64 image including zeros when there are no silhouettes. However, to simplify the statistical analysis, the following mask of each database was constructed: features which contain only zero through all considered databases were removed and their locations in the original set were marked recorded for later display purpose. However, there are feature vectors which still contain zeros for some subjects. Therefore PCA was run on the covariance matrix rather than the correlation matrix.

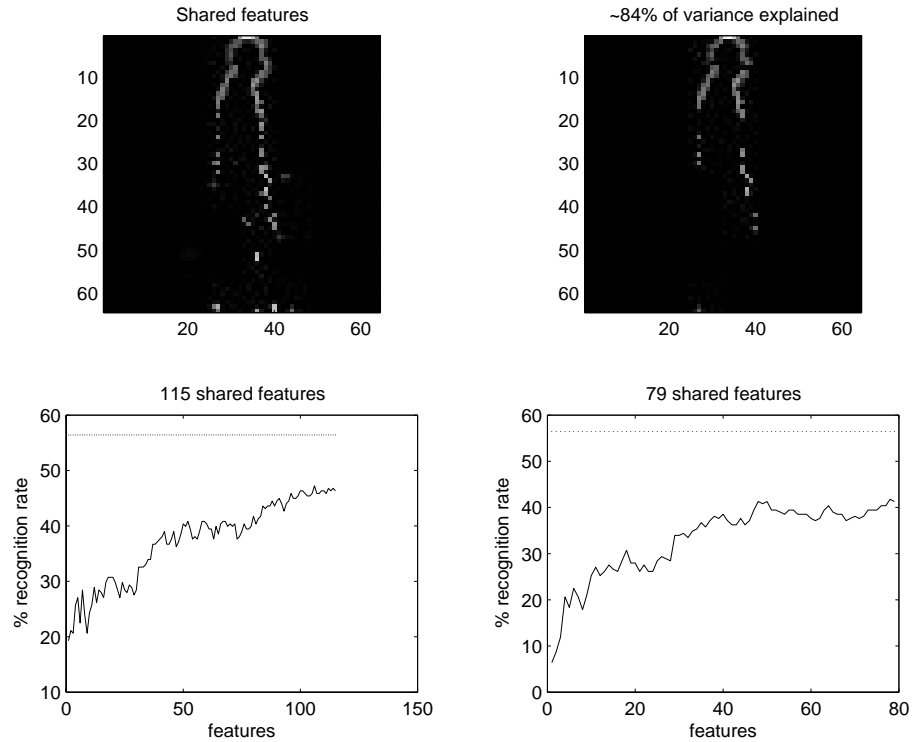


Figure 11 Analyzing the Potency of Silhouette Measures [90]

Two sets of important features, which are the same in all three databases, were considered. First, the features which explain 100% of variance in each data set, i.e. 236, 1001 and 217 features from the three databases. These features contain 115 shared among three datasets important features. Fig. 11 shows the location of shared 115 features on silhouette at the left top picture. The shared features cover the contours of head, body, some legs and some features of arm. To find out which role in recognition these 115 features play, database A was considered as a gallery and database AS was considered as a probe and recognition rates were calculated both for all, 4096 features, and for shared 115 features. The bottom left picture in Fig. 11 shows how the recognition rate changes with adding additional features. Again here the solid line describes dependency of significant features versus recognition rate (46.3% for 115 features), while the dashed line corresponds to recognition rate when all features are considered (56.4%). In this case 17.9% of recognition rate was lost. The further reduction was tried. From each dataset 150 features obtained by PCA earlier were compared and 79 shared features were selected. It was found out that 79 features explain approximately 84% of variance in each databases. These features were projected on silhouette and presented in Fig. 11, top right picture. In this case the most important shared features are contours of the head and body. The recognition rate versus the shared features is presented in the bottom right picture of Fig. 11. In this case

recognition rate for 79 features was 41.3% in comparison to 56.4% for all 4096 features, i.e. a reduction of 26.8%. Practically it means that it is not enough for a differential silhouette to include only static component of gait, in spite of the fact that static components of gait account for 84% of explained variance. Legs play the important role in a differential silhouette, however a practically negligible amount of features describing legs is shared through time, i.e. through all three databases. This then suggests that the motion estimation is crude and should be improved in future analysis.

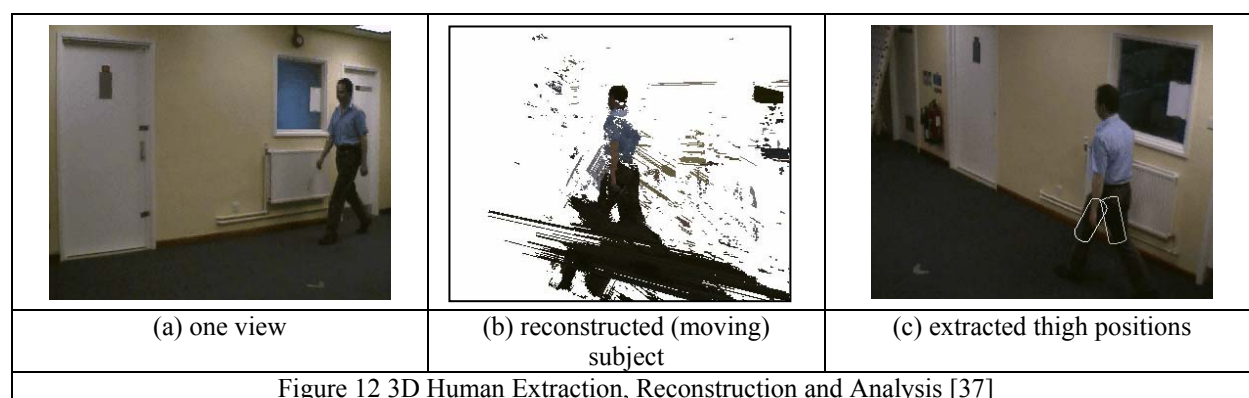
Rank	Indoor Dataset (Database AS)		Outdoor Dataset (Database E)	
	Feature	F-statistic	Feature	F-statistic
1	Lower knee width	239.9	Lower knee width	62.1
2	Ankle width	202.2	Gait frequency	56.4
3	Gait frequency	168.1	Ankle width	47.5
4	Upper knee width	85.7	Upper knee width	46.5
5	Hip width	78.1	Hip width	35.5

Table 5 Potency of Model-Based Gait Measures [88]

The recognition measures were analyzed by using ANOVA and for the performance on the Southampton indoor and outdoor datasets: Database AS and Database E from Tables 1 and 2. This gives for an analysis of potency, shown in Table 5, with the highest F-statistic giving greatest discriminatory capability and hence the highest rank. This is then similar to the analyses of potency of silhouette measures. This analysis suggests that the majority of the system's discriminatory capability is derived from gait frequency (cadence) and from some static shape parameters. Of course, these shape parameters will be highly dependent on clothing, which may limit the utility of performing recognition solely on the basis of these parameters. These results may in part explain why some approaches using primarily static parameters [16] or cadence achieve good recognition capability from few parameters. There is a significant reduction in discriminatory capability in the outdoor dataset compared to the indoor dataset, resulting from the lower extraction accuracy, but there is still a strong case for recognition potential using this data.

4 A Future for Gait?

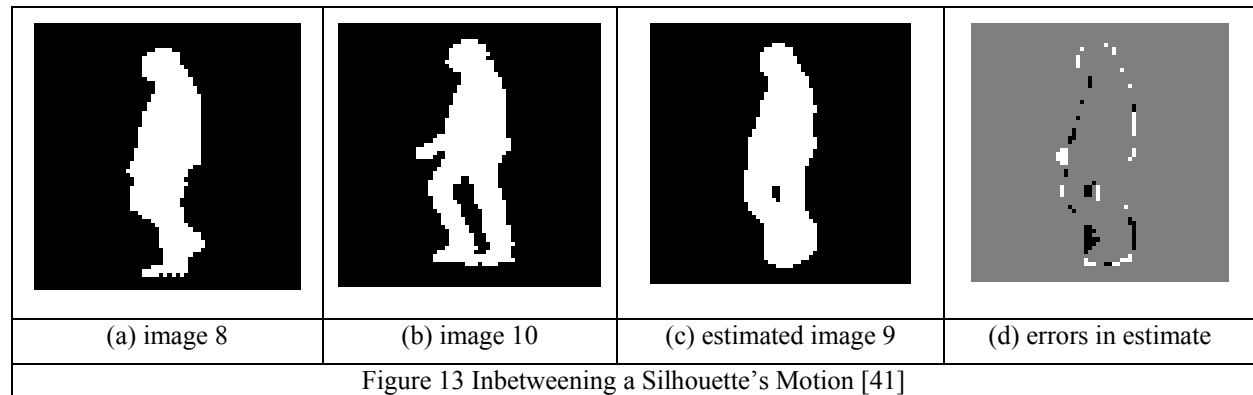
The future for gait is unlikely to be just for biometric purposes. There are medical implications (for markerless gait), forensic implications (scene of crime analysis), and potential links to animation and the film industry. In terms of biometric deployment, it is not unlikely that subject extraction in complex scenarios will require full 3D extraction. In this respect we sought to use our model-based approach to aid 3D subject extraction from multi-view image sequences. In this, we have developed a new representation where reconstruction fidelity is dependent on view direction as well as on distance [37]. One of the viewed images is shown in Fig. 12(a) where a subject walked outside our gait laboratory and under conventional “domestic” illumination. The moving subject was extracted from the background, and reconstructed with our new representation, as shown in Fig. 12(b). A model of ambulatory human motion is then used to determine those points of the object with motion similar to that of the human thigh. The points so labelled are shown in Fig. 12(c) superimposed in 3D in white on one of the original images.



One of the main motivations for 3D analysis concerns the non-linearity associated with gait. With change in viewing angle, the perceived motion of the leg will not be as shown in Fig. 2(b). This motivates analysis for viewpoint correction or generation of analysis that makes gait signatures invariant to view direction. We have shown [38], in a laboratory scenario with images replicating human motion, that we can indeed correct for viewpoint using just the information present in the scene, rather than predefined geometrical analysis. Further, not all of the gait cycle depicted in Fig. 2(b) is actually required for recognition purposes [39]. By analyzing motion captured joint data we have shown on smaller databases that high recognition capability can be achieved with using only a fraction of the gait cycle, as opposed to the complete one.

There are many covariate factors in gait. In this respect, it is encouraging that gait’s progress has been helped, not only in database construction but also by early concentration on covariate factors. Though speed would appear to be a covariate, it has been studied as integral to the basic nature of gait [40]. Further factors including carrying load and wearing different clothing, as to be studied in one of the Southampton databases. Interestingly, increase in resolution can be performed in time as well as in space [41]. Fig. 13 shows the ability to predict new frames from within a sequence of images, a new form of in-betweening specific to gait. Here, a missing frame (no. 10) is

estimated from the ones either side and the motion of the leg is predicted well. This will allow for synchronising of multiple views.



The future also concerns other applications. Essentially, we now have ability to detect and describe gait without subject contact [42]. This lends itself to deeper analysis (for its use is now more convenient) as well as a richer application domain. We hope to deploy our analysis for medical use: we already have better ability to process larger databases automatically and look forward to new insight that this might bring. It could also lead to better animation, for our procedures describe motion with accuracy and allow for analysis of “average” motion as well as individual motion. Since these differ from biometric use, we anticipate that there might be accompanying refinement to our gait description techniques.

5 Conclusions

We firmly believe that by our new technique and by our results, gait continues to show encouraging potential as a biometric. We have constructed some of the largest gait databases, specifically designed to investigate the potential of gait as a biometric. The database allows for: investigation of the basic capability of gait in a laboratory environment; estimation of the capability of gait in unconstrained outdoor scenarios; and investigation of the inter- and intra-class subject variance. The techniques have specifically been designed to provide silhouette based analysis with specificity to gait, by generic formulation tailored to the target application and/or analysis. These techniques describe not only the shape, but also how it moves. We have also extended and demonstrated how a model-based approach can be used to recognise people by the way they walk and by the way they run. These studies continue to confirm that gait is a richer study than it originally appeared. There are many avenues by which the already encouraging potential for gait as a biometric can be improved, and deployed.

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Appendixes

Appendix 1: Publications by Southampton on Automatic Gait Recognition for Human ID at a Distance

Publications marked * are not included in the supplementary volume.

Conference Papers

- * [43] J. B. Hayfron-Acquah, M. S. Nixon and J. N. Carter, Automatic Gait Recognition via the Generalised Symmetry Operator, *BMVA Technical Meeting: Understanding Visual Behaviour*, Jan. 2001
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- * [97] M. S. Nixon, New Biometrics on the Block – Recognition by GAIT, Invited Plenary: *Biometrics 2002*, London 2002
- * [98] J. N. Carter, M. S. Nixon, J. G. Shutler and M. G. Grant, Innovative Techniques in 3D Motion Analysis, *Society for Experimental Biology's Annual Main Meeting*, Southampton 2003
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PhD Theses

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|----------------------------|---|
| [113] K. J. Sharman | PhD 2002: 3D Non-Invasive Multi-View 3D Dynamic Model Extraction |
| [114] J. D. Shutler | PhD 2002: Velocity Moments for Holistic Shape Description of Temporal Features |
| [115] C. Y. Yam | PhD 2002: Model-Based Approaches for Recognising People by the Way they Walk or Run |
| [116] J. B. Hayfron-Acquah | PhD 2003: Automatic Gait Recognition by Symmetry Analysis |
| [117] J. P. Foster | PhD 2003: Automatic Gait Recognition via Area Based Metrics |

- [118] J. H. Yoo PhD 2004: Recognizing Human Gait by Model Driven Statistical Analysis
- * [119] S. P. Prismall PhD: Interframe Prediction for Moving Shapes (submitted)
- * [120] P. Lappas PhD: Extracting Moving Arbitrary Shapes by Evidence Gathering (submitted)
- * [121] N. Spencer PhD: Viewpoint Invariance in Gait (in preparation)
- [122] A. Al-Mazeed PhD: Fusing Complementary Operators for Moving Subject Extraction (in preparation)
- * [123] W. N. Mohd Isa MPhil: Data Modelling for Automatic Gait Recognition (submitted)
- * [124] P. J. Myerscough PhD: Persistent Feature Extraction (in preparation)
- * [125] S. D. Mowbray PhD: Holistic Moving Shape Description (in preparation)
- * [126] R. T. Boston PhD: Viewpoint Invariant Gait Description (in preparation)

Appendix 2: Prizes

NAC/ Mayashita Best Paper Award *International Society of Biomechanics XIXth Congress*, Dunedin New Zealand July 2003 associated with our paper[80]: J-H. Yoo and M. S. Nixon, Markerless Human Gait Analysis via Image Sequences

NDI Student award to J. H. Yoo *International Society of Biomechanics XIXth Congress*, Dunedin New Zealand July 2003 associated with our paper[80]: J-H. Yoo and M. S. Nixon, Markerless Human Gait Analysis via Image Sequences

Literati Club 2004 Highly Commended Award to M. S. Nixon, J. N. Carter, M. G. Grant, L. G. Gordon and J. B. Hayfron-Acquah associated with our paper [110] Automatic Recognition by Gait: Progress and Prospects, *Sensor Review*, **23**(4), 323-331, 2003

Appendix 3: Registered Users of the Southampton HiD Database

(The country is not given for US registrants only.)

1. Ian Comley, University of Bournemouth UK
2. Benjamin Ettori, Electrical Engineering, UCLA
3. Stan Janet, NIST
4. Hongzhe Han, University of Science and Technology, Beijing
5. Pradeep Natarajan, Indian Institute of Technology-Madras, India
6. Ning Huazhong, Institute of Automation, China
7. B. Ho, The Hong Kong Polytechnic University, Hong Kong
8. Yulin, University of Hong Kong, Hong Kong
9. Joni Alon, Computer Science, Boston University
10. Charlie Yuan, Microsoft Research, China
11. Hee-Deok Yang, Korea University, Korea
12. K. L. Jack, ZheJiang University, China
13. Raghu Ram Hiremagalur, Center for Ubiquitous Computing, Arizona State University
14. Dr C K Li, Department of Electronic & Information Engineering, The Hong Kong Polytechnic University, Hong Kong
15. Wai Wong Lok, City University of Hong Kong, Hong Kong
16. Jiayong Zhang, Robotics Institute, CMU
17. Ying Shan, Vision Technology Lab, Sarnoff Corporation, NJ
18. Daniel Kluender Computer Science, Technical University Aachen, Germany
19. Josh Wills, UCSD
20. Ashish Pandey, UCLA
21. Meghna Singh, Electrical and Computer Engineering Department, University of Alberta, Canada.
22. John See, Multimedia University, Cyberjaya, Malaysia
23. Edgar Seemann, ETH Zurich, Switzerland
24. Jeff Boyd , University of Calgary, Canada

25. Shiqi Yu, Mational Laboratory of Pattern Recognition, China
26. J. Z. Wang, Xidian University, Shannxi, China
27. Rogelio A. Alfaro Flores. National Institute of Astrophysics, Puebla, Mexico
28. Ralph Gross, CMU
29. Aaron Bobick, Georgia tech
30. Lily Lee, MIT
31. Mathieu Ilhe, Queen Mary College, University of London UK
32. Toby Lam, Hong Kong Polytechnic, Hong Kong
33. Tianli Yu, Kodak Research Labs, NJ
34. Hanhoon Park, Virtual Reality Lab., Department of ECE, Hanyang University, Korea
35. Nobuyuki Otsu, Univ. of Tokyo, Japan